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A MODIFIED ANT COLONY OPTIMIZATION METHOD FOR SOLVING THE SINGLE TOWER CRANE ALLOCATION PROBLEM

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Abstract: Tower cranes are critical equipment in major construction project due to the high dependence on them for material handling and the high cost associated with their operation. As such, it is very desirable to maximize the efficiency of utilizing tower cranes in different construction operations. To achieve this goal, the problem is formulated as an optimization model with the objective of minimizing the tower crane travel time between supply and demand points. Minimizing the total travel time will in turn lead to reduction in the costs incurred due to transportation of materials. Previous models attempted to optimize the tower crane location using different approaches, such as mathematical techniques and evolutionary algorithms (EAs). However, none of the previous studies considered ant colony (ACO) as an optimization tool despite its notable performance in solving the non-linear quadratic assignment problem. This paper presents a modified ant colony optimization approach (MACA) and its application to the tower crane allocation problem. A comparison was conducted between the performance of ACO and MACA in solving the tower crane allocation problem. The results show that MACA outperforms ACO and offers significant computing capabilities that can also be used for other optimization problems.

1 INTRODUCTION

Tower cranes are essential construction equipment that can be seen in many cities around the world. There are many standards and codes that apply to tower cranes, which can vary depending on the country. Countries like the United States and Canada have adopted consensus standards through organizations such the American Society of Mechanical Engineers (ASME) and the Canadian Standard Association (CSA), which include voluntary practices applicable to tower cranes. Other countries, such as European nations and China, enforce mandatory practices through the European Committee for Standardization (CEN) and Chinese Standards (Shapiro et al. 2010).

Tower cranes are prominent in construction sites because of their versatility in handling various tasks, and their large load capacity. For example, tower cranes has a much larger load capacity compared to mobile cranes. They can carry load at much higher altitudes, and supply many different locations while situated at one location (saving space). However, there are factors that can affect tower crane performance, which include site conditions – obstructions or surrounding buildings – weather conditions, weight of material, motor capacities, height of tower, distance between facilities, and operator's skill. Additionally, tower cranes often come with high costs such as setup and installation fees, rental charges, and disassembly costs. Thus, optimizing the allocation of tower cranes is critical to maximizing their efficiency and minimizing the amount of their idle time.

1.1 Past Models

Several studies have attempted to optimize the allocation of a tower crane in construction sites. Rodriguez-Ramos and Francis (1983) were the first authors to provide a mathematical model for the optimization of the tower cranes' hook travel time. Their model considered the angular and radial movements of the crane for calculating the travel time. Choi and Harris (1991) incorporated the frequency of the movements of the crane to its surrounding facilities. This was an addition to the model presented by Rodriguez-Ramos and Francis and was applied to a theoretical case study in an attempt to optimize the crane's hook travel time. Zhang et al. (1996) utilized Monte Carlo simulation and a refined hook travel time formulation to the tower crane allocation model. The Monte Carlo was used to simulate the delivery sequence and time it takes for the tower crane to service its surrounding facilities. In 1999, Zhang et al. expanded their previous work by accounting for the vertical travel time of the hook as well as considering multiple cranes on site. Tam et al. (2001) presented a tower crane optimization model using a genetic algorithm (GA). This approach was the first model to introduce evolutionary algorithms (EAs) in optimizing the tower crane allocation problem using actual velocity values from site observations. The authors later expanded their research in 2003 and presented a model that combined GA and artificial neural networks (ANN). The end result was a statistical representation of the hoisting time that produced acceptable results. Almost a decade later, Huang et al. (2011) presented a tower crane optimization model using mixed integer linear programming (MILP). Their model has the capacity to find global optimal solution; they demonstrated the great performance of their work in comparison to GAs. Izarry and Karan (2012) combined the advantages of building information modeling (BIM) and geographic information system (GIS) to allocate multiple tower cranes. Their model provided superior site coverage while reducing the possibility of conflicts between the cranes. In 2014, Lien and Cheng presented a model that optimized the tower crane location using another evolutionary approach particle called bee algorithm (PBA). This technique encompassed the best traits from bee algorithm (BA) and particle swarm optimization (PSO). The authors applied their methodology to the case study set by Tam et al. (2001) with optimized quantity of materials for the supply points. Abdelmegid et al. (2015) developed a GA model and incorporated improvements to the previous models in terms of number of cycles, vertical hook travel time, and tower crane base. Marzouk and Abubakr (2015) created a comprehensive framework utilizing GAs and BIM to assist managers and planners with allocating the tower crane and select its appropriate type. Similarly, Wang et al. (2015) utilized BIM with a the firefly algorithm (FA). Their model outputs the final layout for a construction project. Tubaileh (2016) developed and incorporated kinematic and dynamic models to accurately portrait the hoisting operations of the crane. Using simulated annealing (SA) algorithm and the case study by Huang et al. (2011), Tubaileh achieved different results due to the more accurate velocity considerations. Nadoushani et al. (2016) provided a model that incorporated the relationship between the tower crane's lifting capacity and total costs incurred. The authors considered the crane's load capacities as a constraint in their model and optimized the location with MILP. Treviño and Abdel-Raheem (2017) incorporated ant colony optimization (ACO) to the single tower crane allocation problem. Their work was the first to consider the use of this algorithm and it was applied to a case study. \

1.2 Limitations of Previous Models

Although many of these models made significant contributions to the tower crane allocation problem, they were limited in their usefulness due to unrealistic assumptions, calculation errors and discrepancies, and confusing terminology. Rodriguez-Ramos and Francis (1983) used their methodology on simple theoretical problem that did not consider the vertical movements of the crane. The optimization model by Choi and Harris (1991) only accounted for four predetermined positions for the tower crane and failed to consider other available locations. A major weakness in the work by Zhang et al. (1996) was the incorrect formulation of the hook's angular time (Treviño and Abdel-Raheem, 2017). This error has been carried out throughout the literature in many studies except for the Abdelmegid et al. (2015). Zhang et al. (1996) also discussed using an effective algorithm to determine a feasible area where the crane can be positioned, but did not provide any details on the selection of the area. Tam et al. (2001) utilized Gas, but their model contained a number of predetermined tower crane positions that made the selection process somewhat trivial. In the work of Huang et al. (2011), there some discrepancies such as the alpha and beta parameters and the incorrect angular travel time formulation. This creates difficulties to the researchers when trying to recreate their work. Izarry and Karan (2012) did not discuss the cost functions or the objective function in their work.

Lien and Cheng (2014) did not provide details regarding the values of the quantities of materials and used different alpha and beta parameters without explanation. Abdelmegid et al. (2015) developed improvements to the previous tower crane allocation models, but did not clearly explain or illustrate the incorporation of the claimed improvements in their objective function. The model by Nadoushani et al. (2016) incorporated the same angular formulation error that other works used. In addition, they did not provide all data used in their model. When it comes to the usage of ACO by Treviño and Abdel-Raheem (2017), the authors considered each tower crane location as a separate nest, but did not consider communication between the nests of ants. This creates an inefficient system because all nests, regardless of their location with respect to the food source, send out the same number of ants in their search. To illustrate this concept, a hypothetical example is shown in Figure 1.

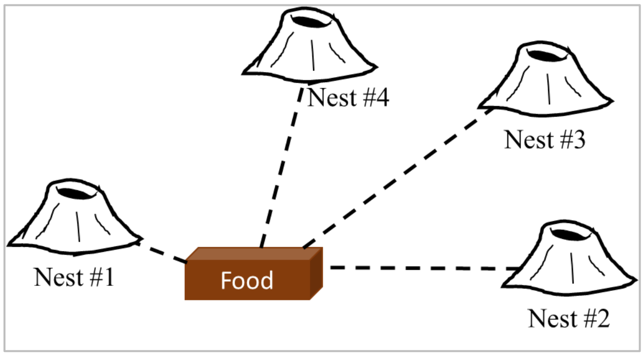


Figure 1.Distance between Nests and Food Source

In the illustration, there are four ant nests and one food source. The nests are at different locations from the food source, but Nest #1 is the closest one. Assuming that all nests are interconnected and cooperate with each other, it would be wasteful for all the ants further from the food source to travel the longer path when the ants in Nest #1 are closer. Thus, utilizing ACO for a tower crane allocation problem with many crane locations presents a special case to be considered.

As such, the objective of this paper is to address this missing piece of information from ACO by providing a modification to the approach and make it suitable to solve these special types of tower crane allocation problems.

1.3 Methodology

In order to achieve the aforementioned objective, the general ACO approach was modified to enhance its performance. This modification, entitled Modified Ant Colony Approach (MACA), incorporated the utilization of a lead ant that provides the missing information to the rest of the ants at different nests. A case study from the literature was selected for the application of both ordinary ACO and MACA. Results and comparisons were made followed by concluding remarks.

2 BACKGROUND

2.1 ACO

Ant colony optimization (ACO) is a swarm-based artificial technique created in 1992 by Marco Dorigo based on the foraging behavior of ant colonies as they search for food. Ants are mostly blind, so they deposit pheromone as they travel to guide themselves. When an ant finds food, it uses its pheromone trail to return to the nest while depositing more pheromone. The ant that gets to the source of food fast – the ant with the shortest path – tends to deposit more pheromone than the rest of ants. This leaves a strong pheromone concentration on its route. Eventually, nearby ants detect the higher concentration and converge towards the shortest path.

2.2 MACA

MACA follows the ACO theory with a few exceptions. The principal difference is that MACA is based on the assumption that there are several nests that accommodate the members of the ant colony. All ant nests cooperate and exchange information to achieve a goal. This exchange of information is done with the aid of an agent called “Lead Ant”. The ants get out of their nests searching for food, the lead ant gathers performance information on each of the nests and ranks them according to their best solution. Afterwards, the lead ant manipulates and distributes the ant population in a way such that the higher ranked nests accommodate more ants. This process aids the ant population converge to the nest that leads to the shortest path (best solution). A flowchart illustrating the general idea of this approach is shown in Figure 2.

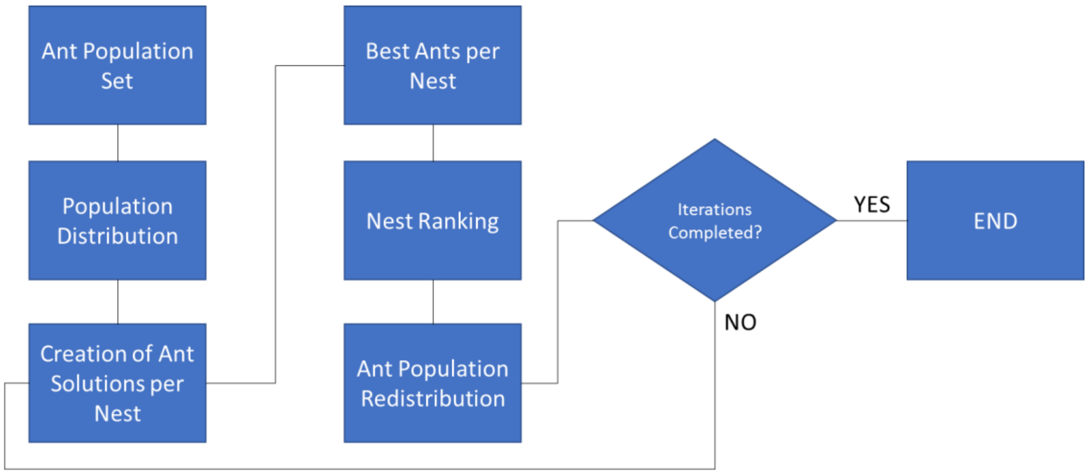
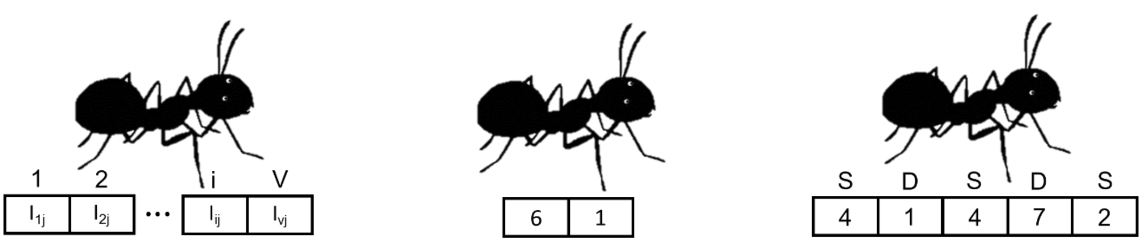


Figure 2. Flowchart of MACA general steps

The generic ACO and MACA follow six basic steps (Abdel-Raheem et al. 2013):

1. **Generating trial solutions.** A population of ants is created. Each ant has a number of variables, V, and each variable encompasses an option, j, and a pheromone concentration. In MACA, the a lead ant is additionally generated. To solve the tower crane allocation model, the ant can be modeled in a number of distinct ways as shown in Figure 3. For example, one way is to simply allocate the tower crane coordinates to the ant variables, such as in Figure 3b. Another way is to have the ant variables contain the facilities in need of service by the crane, as seen in Figure 3c. This string of facilities, or ant tour, would then represent a certain sequence of deliveries that the crane performs in the given order. As such, the variables are the series of supply and demand facilities in order. The lead ant can be modeled to give binary instructions for determining which nest receives part of the ant population as seen in Figure 4, where “0” represents an empty nest and “1” indicates the presence of ants.



a. Theoretical ant variables b. Tower crane location variables c. Supply-demand sequence

Figure 3. Ant variables in theory and related to tower crane allocation problem

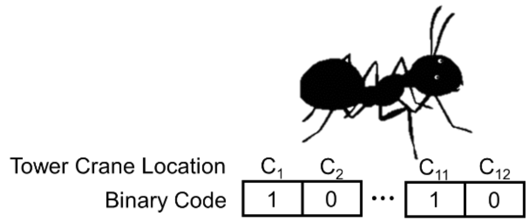


Figure 4. Lead Ant decision making

2. **Heuristic Information.** This step designates a piece of information that aims to guide the ant during its search. By giving the ant hints about the problem's optimal solution, the ant can shorter time to find it. Thus, this information changes depending on the problem and its nature. For example, if the objective function is maximization, the ant's total tour length can be taken as the heuristic information. In the tower crane allocation problem, the total distance between the crane and surrounding facilities can be used. This step is the same for both ACO and MACA.

3. **Evaluation.** In ACO, the ants undergo an evaluation process by comparing their values to the problem's objective function. In MACA, the ants follow the same evaluation process, but the lead ant might have a different objective function than the colonies. To limit the population of ants in the nests with low merit, Equation 1 and 2 can be used, where $TC\ (i)$ is the value of the nest N and $C(i)$ is a binary variable to help with the distribution process.

   [1] $\sum_{i=1}^{N} TC\ (i) * C(i)$

   [2] $C(i) = \sum_{i=1}^{N} \begin{cases} 1\ if\ Nest\ (i)\ is\ selected \\ 0\ otherwise \end{cases}$

   Common objectives for the tower crane allocation problem include the minimization of the total costs and the hook travel time.

4. **Pheromone Update.** At the end of the tour, the algorithm update the pheromone concentration on the paths selected by the ants by allocating more pheromone to the better paths. This pheromone update is performed using Equation 3,

   [3] $\tau_{ij}(t) = \rho * \tau_{ij}(t-1) + \Delta\tau_{ij}$

   where $\tau_{ij}(t)$ is the new pheromone concentration at iteration t, ρ is the pheromone evaporation rate, $\tau_{ij}(t-1)$ is the pheromone concentration associated with option j of variable i at the previous iteration, and $\Delta\tau_{ij}$ is the change in pheromone concentration. The pheromone evaporation rate prevents early convergence and allows ants to explore other routes. The change in pheromone concentration can be calculated using Equation 4,

   [4] $\Delta\tau_{ij} = \sum_{k=1}^{M} \begin{cases} \frac{R}{f(\varphi)k}\ if\ option\ l_{ij}\ is\ selected \\ 0\ otherwise \end{cases}$

   where R is the pheromone reward factor, $f(\varphi)k$ is the objective function value of ant k, and M is the ant population.

   In MACA, the pheromone concentration is distributed according to the relative fitness of all ants. For example, if there are three tower crane locations (nests) with values of 10, 20, and 30, respectively, and the objective is maximization, the relative fitness of each nest is 50/10, 50/20, and 50/30, respectively. Obtaining a percentage based on the total would result in 55%, 27%, and 18% for the three locations, respectively.

5. **Probability Update.** Each option, j, is associated with a certain selection probability. This probability is determined by Equation 5,

   [5] $P_{ij}(k,t) = \frac{\tau_{ij}(t)^{\alpha} * \eta_{ij}{}^{\beta}}{\sum \tau_{ij}(t)^{\alpha} * \eta_{ij}{}^{\beta}}$

   where $P_{ij}(k,t)$ is the probability of ant, k, choosing option j for variable i at iteration t, $\tau_{ij}(t)$ is the pheromone concentration associated with option l_{ij} at iteration t, η_{ij} is the heuristic value, and α and β are factors that reflect importance of either pheromone concentration or heuristic information in finding the optimal solution (Elbeltagi et al. 2005). This step is the same for ACO and MACA.

6. **Termination.** The algorithm terminates if it meets a stopping criteria. This can be after an executed number of iterations or a specified interval of time.

3 ACO AND MACA MODELING AND IMPLEMENTATION

3.1 Case Study

A case study from the literature presented by Huang et al. (2011) was selected for implementation and the comparison of both ACO and MACA. The objective in this tower crane model is to minimize the total costs associated with the travel time of the crane based on Equation 6,

[6] $Minimize\ TC = \sum_i^I \sum_j^J \sum_l^L T_{i,j}^k * Q_{l,j} * C$

where $T_{i,j}^k$ is the total transportation time between supply i and demand j from tower crane located at position k, $Q_{l,j}$ is the quantity of material l required at demand j, and C is the cost per unit time.

The total transportation time $T_{i,j}^k$ can be calculated using Equation 7,

[7] $T_{i,j}^k = \gamma\{Max(T_{hij}{}^k, T_{vij}) + \beta * Min(T_{hij}{}^k, T_{vij})\}$

where γ is a factor that describes the difficulties the crane operator might encounter, $T_{hij}{}^k$ is the horizontal travel time of the hook by tower crane k moving from supply i to demand j, β is a factor that describes how consecutive or simultaneous the movements of the crane are along the horizontal and vertical planes, and T_{vij} is the vertical hoisting time experience by the crane lifting a load from supply i to demand j.

Further, the horizontal and vertical components can be seen in Equations 8 and 9, respectively,

[8] $T_{h\,(i,j)}^k = Max(T_{r\,(i,j)}^k, T_{\omega\,(i,j)}^k) + \alpha * Min(T_{r\,(i,j)}^k, T_{\omega\,(i,j)}^k)$

[9] $T_{v\,(i,j)}^k = \frac{S_j{}^z - D_j{}^z}{V_h}$

where $T_{r\,i,j}^k$ is the radial travel time of the trolley from tower crane at location k moving from supply i to demand j, $T_{\omega\,i,j}^k$ represents the angular travel time of the crane rotating from supply i to demand j, α is a factor that denotes how consecutive or simultaneous the crane movements are along the horizontal plane, $S_j{}^z$ and $D_j{}^z$ represent the height of both the supply and demand facilities, and V_h is the hoisting velocity of the crane. Both α and β can have values from 0 (fully simultaneous movement) to 1 (complete consecutive movements) (Zhang et al. 1999).

The radial and angular travel time formulations are shown in Equation 10 and 11, respectively,

[10] $T_{r\,(i,j)}^k = \frac{|\rho(D_j, Cr_k) - \rho(S_i, Cr_k)|}{V_r}$

[11] $T^{k}_{\omega\,(i,j)} = \frac{1}{V_\omega} * arccos\left(\frac{\rho(D_j,Cr_k)^2+\rho(S_i,Cr_k)^2-l_{i,j}{}^2}{2*\rho(D_j,Cr_k)*\rho(S_i,Cr_k)}\right)$

where $\rho(D_j, Cr_k)$ is the linear, Cartesian distance between crane location k to demand j, $\rho(S_i, Cr_k)$ is the distance from the crane k to supply i, V_r and V_ω are the radial and angular velocities, respectively, and $l_{i,j}$ is the distance between supply i and demand j. It is important to note that Equation 9 is based on the corrected formulation from Treviño and Abdel-Raheem (2017).

The case study consisted of 12 predetermined tower crane locations and nine predetermined supply and demand points. Material quantities were taken as 10, 20, and 30 for material type 1, 2, and 3, respectively. The unit cost, C, was \$1.92 per minute and the hoisting, radial, and angular velocities are 60 meters/min, 53.3 meters/min, and 7.57 rad/min respectively. The hypothetical site plan from the case study, where each nest represents a tower crane location and the supply and demand are the sources of food is shown in Figure 5.

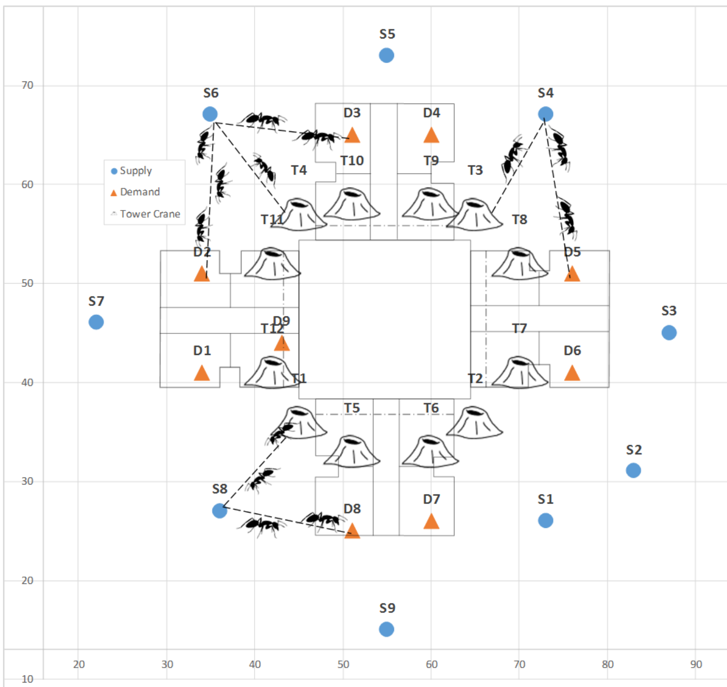


Figure 5.Case study site plan (Huang et al. 2011)

3.2 Ant Modeling

The modeling of the ant is the same in ACO and MACA, as shown in Figure 6. Each ant has three variables that represent the three material types available and each variable holds the supply points that will be used to supply all demands. If a supply is selected in a variable, however, it cannot be used to supply the remaining demand points for the same ant.

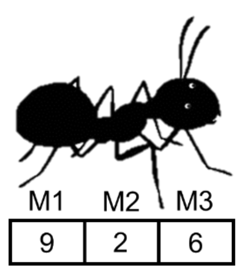


Figure 6. Ant solution example

In MACA, it is important to note that the pheromone update is done per nest, and pheromone cannot be added to the same supply point chosen in two different nests. For example, if an ant in Nest 1 selects supply 1 for its first variable and deposits pheromone in that option, an ant in Nest 2 selecting supply 1 for its first variable will not be adding pheromone to that same option. This constraint is illustrated in Figure 7.

Figure 7. Pheromone repetition for Nest 1 and Nest 2

3.3 Ant Parameters

In this problem, the goal is to use the smallest possible ant population to attain the best possible solution. Through trial and error, the ant parameters chosen for both the basic ACO approach and MACA were an initial ant population of 75 ants per nest, an evaporation rate (ρ) of 0.4, a reward factor (R) of 5, and an α and β values of 1.6 and 1.0, respectively. As for the number of iterations, both algorithms were left to run until they reached the global optimum solution. The respective number of iterations used by each algorithm was recorded to compare the performance. The heuristic information for both algorithms was taken as the inverse of the total distance between the tower crane and supply facilities.

It should be noted that the number of ants per nest in MACA varies from one iteration to another based on the performance of the ants in each nest. The lead ant supervises the performance of ants in all nests. Based on the performance of ants in each location, the lead ants decide on the number of ants to be allocated in each nest. The nest whose ants achieve better values compared to the ants in other nests gets more ants in the next iteration. This is the key concept in MACA, which aims at the efficient utilization of the available limited resources (ants) to get the best possible results. This is accomplished by redistributing the resources among search points relative to their potential to lead to the global optimal solution rather than using a uniform distribution of population as in traditional ACO.

4 RESULTS

Both ACO and MACA were developed using VBA. The codes were executed on a machine with a 3.40GHz processor and 4 MB of ram. The ACO algorithm and MACA metaheuristic reached the best solution of $504.76 at nest 8 (tower crane location 8) in an average time of 10 runs of 1.335 and 0.891 seconds, respectively, using the abovementioned parameters, see Figure 8. The results summary of the runs is shown in Table 1. MACA proved to be a superior alternative approach to traditional ACO for this problem as it took less total number of ants, iterations, and time to reach the optimal solution.

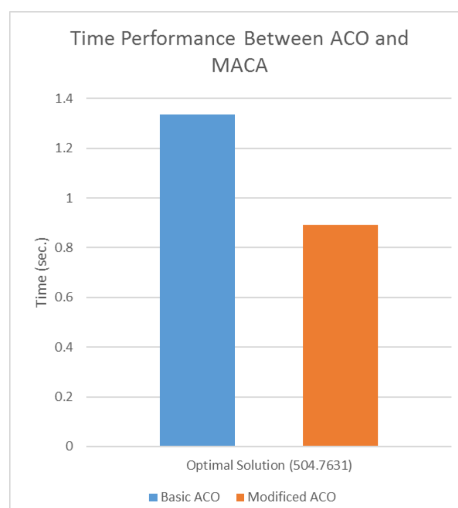


Figure 8. Time difference between ACO and MACA

5 CONCLUSIONS

This paper presented the tower crane allocation problem as well as the previous ACO model that was developed by the authors to model it. The paper discusses the limitations of the previous model, and introduces a new modified version of the traditional ant colony optimization algorithm that was developed to account for the previous model limitations. A case study from the literature was used for the application of both generic ACO and modified approach. Results show a significant advantage in terms of time when utilizing MACA as opposed to traditional ACO to solve this allocation problem. Furthermore, results show a promising potential for MACA to be used for other complex optimization problems.

Table 1. Best ant values and distribution in different runs

Optimization Technique	Number of Iterations	Total Number of Ants	Time (sec.)	Optimal Solution
Basic ACO	5	4500	1.656	504.763
	2	1800	0.734	504.763
	4	3600	1.398	504.763
	5	4500	1.828	504.763
	6	5400	2.039	504.763
	4	3600	1.359	504.763
	5	4500	1.727	504.763
	2	1800	0.727	504.763
	4	3600	1.430	504.763
	1	900	0.453	504.763
Modified ACO	2	1801	0.672	504.763
	5	4500	1.531	504.763
	2	1800	0.750	504.763
	1	900	0.438	504.763
	1	900	0.391	504.763
	8	7199	2.328	504.763
	4	3600	1.328	504.763
	1	900	0.531	504.763
	1	900	0.328	504.763
	2	1802	0.609	504.763

6 FUTURE WORK

Future research on this approach would be its application to other complex optimization problems and actual construction projects.

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